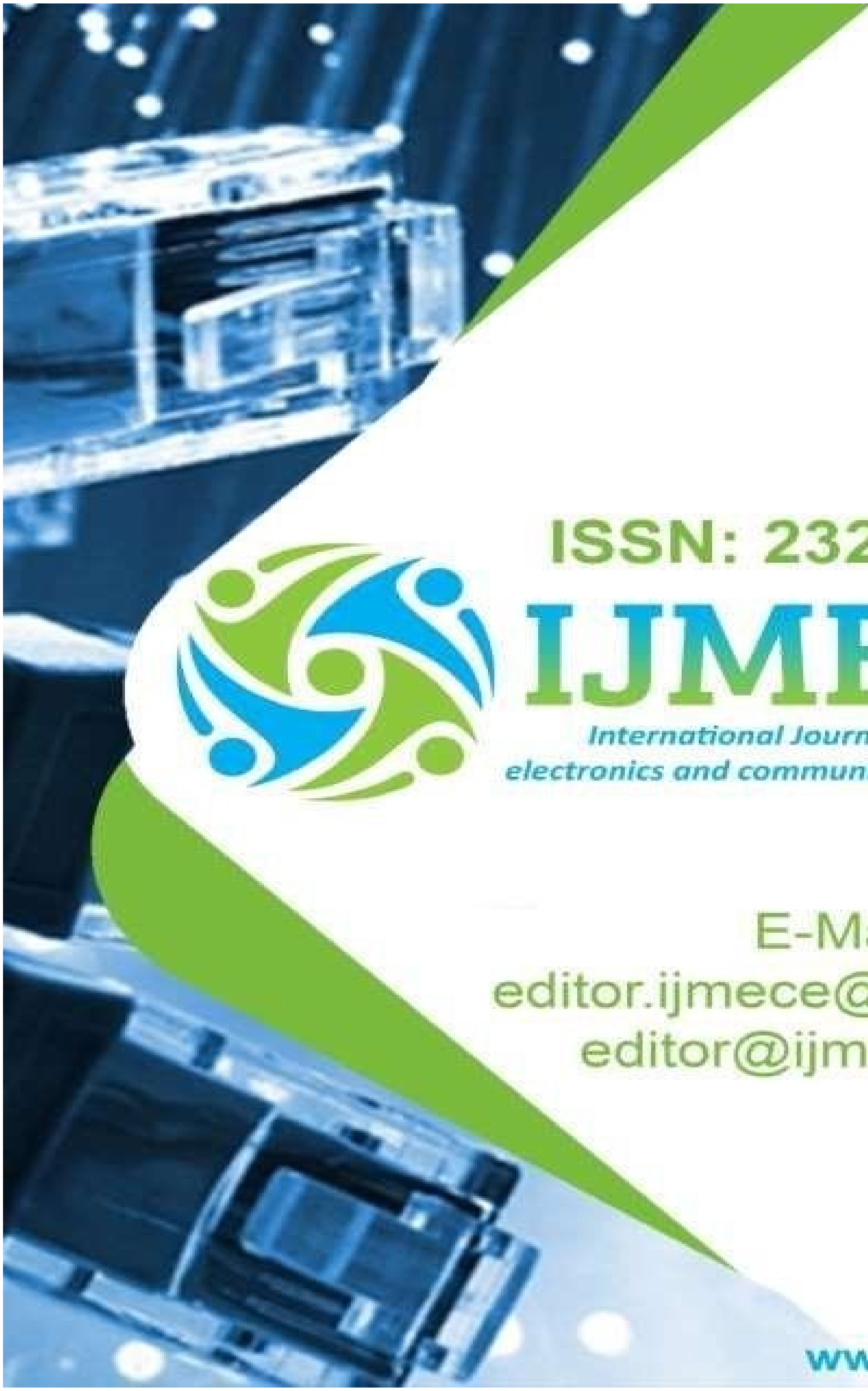

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Uses artificial intelligence to determine a kid's age from a brain MRI scan if the youngster is less than three years old.

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ABSTRACT

The established radiological methods for estimating unknown age in children and adolescents are based on the visual examination of bone ossification in X-ray images of the hand. Our group has begun developing fully automatic age estimation methods from 3D MRI scans of the hand in order to simultaneously overcome the problems of radiological methods, such as exposure to ionizing radiation, the need to define new, MRI-specific staging systems, and the examiner's subjective bias. The current study provides a theoretical foundation for understanding the nonlinear regression problem of biological age estimation and chronological age approximation. Based on this theoretical foundation, we thoroughly evaluate machine learning methods (random forests, deep convolutional neural networks that use different simplifications of the image information as an input for learning. Trained on a large dataset of 328 MR images, we compare the performance of various input strategies and show unprecedented results. We estimate biological age with a mean absolute error of 0.37±0.51 years for subjects under 18 years old, indicating that bone ossification has not yet reached saturation.Finally, we validate our findings by adapting our best performing method to 2D images and applying it to a publicly available dataset of X-ray images, showing that we are in line with the state-of-the-art automatic methods for this task.

KEYWORDS: Biological age (BA),Age estimation, regression, Convolutional neural network, Random forest

INTRODUCTION

The progression of physical maturation in young people can be used as a biological marker for aging. Estimating biological age (BA) from physical development is thus a critical topic in both clinical and forensic medicine applications. In clinical medicine, BA estimation is motivated by the diagnosis of endocrinological diseases such as accelerated or delayed development in adolescents, or for optimally planning the time-point of pediatric orthopedic surgery interventions while bones are still growing. Examples of such interventions include correcting leg length discrepancies and performing spinal deformity correction surgery .In legal medicine, when identification documents for children or adolescents are missing, as may be the case in asylum-seeking procedures or criminal investigations, estimation of physical maturation is used as an approximation to assess unknown chronological age (CA).

Established radiological methods for estimating physical maturation rely on the visual examination of bone ossification in X-ray images .Ossification is best performed on long bones, and radiologists primarily examine hand bones due to the large number of assessable bones visible in X-ray images of this anatomical region, as well as the fact that aging progresses at different rates for all hand bones. More specifically, carpal and distal phalanges are the first bones to complete ossification, while maturation in the radius and ulna can take up to 18 years. The level of ossification assessed by the radiologist is used to estimate an individual's physiological maturity, which is then quantified by comparing its maturity to the age of subjects in the reference atlas who had the same level of ossification. In the rest of this paper, we will refer to this quantification as biological age as estimated by radiologists (BAR).

METHODOLOGY

Although the TW2 method is more objective and slightly more accurate than the GP method, it is used less frequently in clinical and forensic practice due to its longer time requirements.

Aiming for reliable and accurate estimation without subjec-tive influence of the examiner,automated image analysis meth-ods for age estimation were developed notably, the BoneXpert method employs Active Appearance Models to automatically segment hand bones and principal component analysis to reduce the dimensionality of age-relevant shape and appearance feature information before regressing age. To reproduce the BAR, the fusion of individual estimations is calibrated using the same pre-defined nonlinear function developed for TW2. Deep convolutional neural networks (DCNN) have recently been shown to be extremely successful in solving a variety of machine learning and computer vision problems, owing to their ability to automatically learn task-relevant features from large training datasets. They investigated several deep learning architectures for automatically assessing BAR on a publicly available dataset of subjects of various genders and ethnicities aged 0 to 18.

The Radiological Society of North America (RSNA) recently organized a Pediatric Bone Age Challenge to demonstrate the potential of machine learning and artificial intelligence in learning BAR from 14,036 clinical hand radiographs and reports from two children's hospitals. The winner of the competition used the deep Inception V3 CNN with additional gender formation, which was evaluated on 200 images with reference BAR annotation performed by three radiologists.

Aseveredrawbackofradiographicageestimationtechniquesisexposuretoionizingradiation.This drawback is exacerbated in legal medicine applications, where several anatomical structures are examined to extend the age estimation range beyond 18 years, such as for adolescent asylum seekers who lack valid identification documents. For such multi-factorial age estimation, dental radiography of wisdom teeth and computed tomography of clavicle bones are used in addition to hand radiographs, significantly increasing the amount of ionizing radiation required. Thus, MRI-specific radiological staging schemes are currently receiving a lot of research attention. To the best of our knowledge, our group is the only one developing automated MRI-based methods for age estimation in order to simultaneously overcome the problems of exposure to ionizing radiation, the need to define new, MRI-specific staging systems, and the examiner's subjective influence. They used a random forest (RF) to analyze data from adolescents.

In recent years, our group has begun the development of fully automatic age estimation methods from 3D MRI scans, in order to simultaneously overcome problems of ionizing radiation exposure, the need to define new, MRI-specific staging systems, and the elimination of the examiner's subjective influence. In this study, we improve our MRI-based age estimation strategies and thoroughly test their performance on a large dataset. Thus, we extend our previous work in the following areas:

We provide a theoretical foundation for understanding the high-dimensional, nonlinear regression problem of estimating biological age (BA) from 3D hand MRIs.

We thoroughly investigate various strategies for simplifying this regression problem by comparing the performance of RFs using handcrafted feature extraction with DCNNs promising automatic learning of task-specific filters

• We evaluated both approaches on a larger dataset of 328 subjects.

• Our DCNN approach significantly improves on previous age estimation results and provides a cutting-edge method for 3D handMRI.

CONCLUSION

This study presented an objective software-based solution for automatically estimating age from 3D MRI scans of the hand. Unlike other groups working on automatic age estimation, our approach does not require the use of ionizing radiation, which is critical in legal medicine applications involving healthy individuals. Our thorough evaluation of various machine learning methods revealed that our DCNN-based regression approach outperforms previous MRI-based methods. Furthermore, when adapted for 2D images, the method is consistent with cutting-edge methods developed specifically for X-ray data.

On our 328-image MRI dataset, we demonstrated that introducing prior knowledge about where age-relevant anatomical information is located helps the DCNN learn this high-dimensional nonlinear regression problem. Nonetheless, it may be assumed that in the presence of a much larger training dataset, the need for such a preprocessing step could be overcome, as indicated by the results of the recent RSNA challenge on age estimation from 14,0362 DhandX-ray images, where the best deep learning methods used the entire hand image as input.

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